Research Article

Fault Diagnosis Method of Rotating Machinery Based on Collaborative Hybrid Metaheuristic Algorithm to Optimize VMD

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With the improvement of the complexity and reliability of mechanical equipment, it has been difficult for the commonly used variational modal decomposition method of vibration signal of rotating machinery to meet the current practical engineering requirements. In order to further improve the adaptability, processing efficiency, and robustness of rotating machinery fault diagnosis methods, a collaborative hybrid element heuristic to multiobjective optimization algorithm is introduced in this paper. Combined with variational modal decomposition (VMD) method, the fault diagnosis method of rolling bearing under complex working conditions is studied. This paper mainly uses a collaborative hybrid metaheuristic algorithm to improve the nondominated sorting genetic algorithm II (NSGA II) and multiobjective particle swarm optimization (MOPSO), which improves the convergence efficiency of multiobjective optimization method and solves the problem of uneven distribution of optimal solutions. Then, the improved multiobjective optimization algorithm is combined with VMD to solve the problem of parameter selection of the VMD method under complex working conditions of rotating machinery. At the same time, the variation relationship between various signal features and VMD decomposition results is compared and studied, and the features with good effect are taken as the objective function of the optimization algorithm; the ability of denoising and feature extraction of VMD in rotating machinery fault diagnosis is improved. In this paper, the proposed method is explored by using analog signals and experimental data of rolling bearings. Through comparison, the improvement of adaptive ability, operation speed, and robustness of the proposed method in rotating machinery fault diagnosis is verified.

1. Introduction

With the mass production and operation of various modern mechanical equipment, the safety and reliability requirements of modern industry for mechanical equipment are also increasing [1]. As the most widely used rotating mechanical component in various mechanical equipment, rolling bearing plays an important supporting role in the mechanical system. Because it undertakes most of the load of mechanical equipment, the failure rate of various mechanical components is also high [2]. If the fault of rolling bearing is light, it will reduce the operation efficiency of equipment. If it is serious, it may lead to complete failure of mechanical equipment and even serious engineering accidents. According to statistics, in various mechanical equipment failure cases in recent years, more than 70% are caused by rotating mechanical parts such as rolling bearing and gear failure [3]. Therefore, the research on rolling bearing fault method is of great significance [4].

At present, the most commonly used fault diagnosis method for rotating parts of mechanical equipment is through vibration signal analysis of mechanical equipment [5]. The time-frequency characteristic of vibration signal is the key to solve the problem of rotating machinery fault diagnosis [6]. The classical methods and theories include wavelet transform (WT), empirical mode decomposition (EMD), and variational mode decomposition (VMD) [7]. In recent years, relevant scholars have also optimized and improved these classical methods to make them more in line with the current engineering safety and reliability requirements. For example, Chen et al. proposed an improved VMD method based on fractional Fourier transform (FRFT), which makes VMD more sensitive to periodic pulses, so that the early fault features of rolling bearings
can be extracted [8]. Zhu et al. improved the WT method by using the double evaluation multiscale template matching algorithm, which greatly improved the operation speed and performance of the WT method [9]. Chen et al. combined EMD with deep neural network (DNN) and proposed an EMD-DNN method for acceleration signal noise reduction, which achieved better results in acceleration data baseline correction [10]. Therefore, the classical signal time-frequency domain analysis methods can still be further optimized to solve various practical engineering problems. This paper will start with VMD [11], which is the most commonly used fault diagnosis of rolling bearing, and proposes a fault state detection method which can adaptively distinguish the actual working conditions of rolling bearing, so as to improve the safety and reliability of rotating machinery equipment [12].

Although the VMD method can efficiently complete the modal decomposition of vibration signals, the eigenmode functions (IMFs) obtained by the decomposition often have modal aliasing or underfitting [13]. Through the research and exploration of scholars, it is found that the unsatisfactory result of the VMD method is mainly due to the number of parameter modes K and the quadratic penalty term α. Due to improper selection, when K is less than the actual number of modes, it will lead to the decomposition result of multimodal aliasing. When K is greater than the actual number of modes, it will lead to overdecomposition. The noise component is decomposed as one of the IMFs, resulting in analysis errors; α will affect the division criteria of frequency band in the decomposition process, affect the decomposition between adjacent modes, and also cause mode aliasing [14]. Therefore, to obtain the optimal VMD parameters, it is necessary to optimize the parameter selection method of VMD [15]. At present, there are many studies on VMD parameter optimization methods. For example, Li et al. proposed a PSO optimization method for VMD parameter selection, combined with VMD and LSSVM classification methods to complete the early fault diagnosis of rolling bearing signals [16]. Kumar et al. extracted the instantaneous frequency feature of rolling bearing signal through Fourier compression transform (FSST) and took the feature as the objective function of genetic algorithm (GA), so as to select the optimal parameters of VMD [17]. Wang et al. proposed a method of spatial scale, which adaptively obtains the optimal parameters of VMD by extracting signal features and has been verified on the gearbox fault data set [18]. Xu and Hu took the minimum average mutual information (GWOMI) as the objective function of gray wolf optimization algorithm (GWO), optimized the parameters of VMD, and achieved good vibration signal analysis results [19].

Through the research of the above scholars, it can be found that the best VMD parameter results can be obtained through the multiobjective optimization algorithm. In this paper, a more efficient multiobjective optimization algorithm—the cooperative optimization algorithm of nondominated genetic and multiobjective particle swarm optimization (NSGA II MOPSO)— is used to optimize the two parameters of VMD; as a collaborative hybrid heuristic optimization algorithm, this optimization method can combine the advantages of the two optimization algorithms. The performance of the NSGA II MOPSO method used in this paper in multiparameter optimization has also been verified [20]. By combining the generation by generation optimization scheme of NSGA II with the rapid optimization ability of MOPSO, this method can realize the rapid and accurate optimization of multiobjective parameters [21]. At present, it has been applied to multiparameter optimization problems in some projects [22]. In addition, in order to obtain the optimal parameters in rolling bearing fault diagnosis, it is also necessary to provide a reasonable objective function for the multiobjective optimization algorithm [23]. Through the vibration signal, we can obtain a variety of signal time-frequency domain characteristic parameters, such as vibration signal extraction method based on spectrum index [24], time-frequency spectrum extraction method [25], information extraction method of multifeature fusion, and the extraction method of signal entropy [26]. Combined with the decomposition results of the VMD method, this paper will also study the change relationship between eigenmode function and relevant features, so as to select dominant features, combine them to form new feature indexes, and improve the VMD processing method for rolling bearing vibration signal [27]. Starting from the optimization of variational modal decomposition parameters, this paper proposes a new time-frequency characteristic index to reflect the fault state of rolling bearing and completes the selection of variational modal decomposition parameters of rolling bearing vibration signal by the NSGA II MOPSO method. The multiobjective optimization method used in this paper has stronger adaptability and also ensures the efficiency of the method, the accuracy of the results, and robustness.

In this paper, the research process is complete from theoretical research to method verification, as well as improved methods and experimental verification. In the second part, the basic theories and methods of this paper are introduced in detail, such as VMD and the principle of multiobjective optimization algorithm. Then, starting from the theoretical research, the proposed method assumptions are introduced in detail in the third part of the article, and the method is verified and improved through the analog signal, forming a complete feasible scheme. In the fourth part, the method is verified by using the actually collected vibration signals of rolling bearing, and the method is compared with ergodic method, nondominated sorting genetic algorithm, and multiobjective particle swarm optimization method to verify the efficiency and robustness of the proposed method. Finally, the content of the article is summarized.

2. Involving Methods

2.1. Variational Modal Decomposition (VMD). VMD is a common signal mode decomposition method. The VMD method can iteratively decompose complex multimodal signals into eigenmodes (IMF) with different spectral components [28]. In mechanical fault diagnosis, the IMFs can be obtained by VMD of the vibration signal generated by the
mechanical system. The specific components of the mechanical system can be known by analyzing the obtained IMFs, so as to judge the specific state of the mechanical system [29].

In the VMD method, the IMF obtained by initial signal decomposition can be expressed as

\[ Y = \sum_k u_k(t) + \text{residual}. \]  

(1)

The \( k \)th IMF obtained by decomposition can be expressed as

\[ u_k(t) = A_k(t) \cos(\phi_k(t)), \]  

(2)

where \( A_k(t) \) represents the amplitude of the \( k \)th IMF at time \( t \), \( \phi_k(t) \) represents the nonattenuation function of the \( k \)th IMF at time \( t \), and the derivative of \( \phi_k(t) \) represents the instantaneous frequency at time \( t \).

The VMD method is essentially a solution method of a constrained variational problem. In the process of processing vibration signals, the constrained variational problem required by this method can be expressed as

\[ \min_{\{u_k\}, \{\omega_k\}, \lambda} \left\{ \sum_k \left\| \partial_t \left[ (\delta(t) + \frac{j}{\pi t}) \cdot u_k(t) \right] e^{-j\omega_k t} \right\|^2 \right\}, \]  

(3)

where \( \delta(t) \) represents the Dirac function at time \( t \), \( \partial_t \) represents the gradient function obeyed by \( t \), and \( e^{-j\omega_k t} \) is the complex exponent. In order to solve the constrained variational problem, the quadratic penalty term and Lagrange multiplier are added on the basis of equation (3), and the constrained variational solution function is obtained:

\[ \ell(u_k, \omega_k, \lambda) = a \sum_k \left\| \partial_t \left[ (\delta(t) + \frac{j}{\pi t}) \cdot u_k(t) \right] e^{-j\omega_k t} \right\|^2 + \left\| f(t) - \sum_k u_k(t) \right\|^2 + \lambda \left( \delta(t), y(t) - \sum_k u_k(t) \right). \]  

(4)

where \( \{u_k\} \) and \( \{\omega_k\} \) represent each IMF and its center frequency, respectively. The extracted IMF and its center frequency can be updated and obtained iteratively through equations (5) and (6).

\[ \hat{U}_k^{n+1}(\omega) \leftarrow \frac{\hat{Y}(\omega) \sum_{i<k} \hat{U}_k^{n+1}(\omega) - \sum_{i<k} \hat{U}_k^n(\omega)}{1 + 2\alpha (\omega - \omega_k^n)^2}, \]  

(5)

\[ \omega_k^{n+1} = \frac{\int_{-\infty}^{\infty} \omega \left| \hat{U}_k^{n+1}(\omega) \right|^2 d\omega}{\int_{-\infty}^{\infty} \left| \hat{U}_k^{n+1}(\omega) \right|^2 d\omega}. \]  

(6)

In the above formula, \( \hat{U}_k^{n+1}(\omega) \) represents the Fourier transform frequency domain of the \( k \)th IMF obtained by decomposition; \( \hat{Y}(\omega) \) and \( \hat{\Lambda}^n(\omega) \) represent the Fourier transform forms of \( y(t) \) and \( \Lambda^n(t) \), respectively. Based on the above conditions, the Fourier transform update formula of the Lagrange operator is

\[ \hat{\Lambda}^{n+1}(\omega) \leftarrow \hat{\Lambda}^n(\omega) + \tau \left( \hat{Y}(\omega) - \sum_k \hat{U}_k^{n+1}(\omega) \right). \]  

(7)

\( \tau \) in the formula represents the constraint strength. The iteration termination condition of VMD can be expressed by equation (8), where \( \varepsilon \) represents the minimum accuracy value and \( \varepsilon = 10^{-7} \) is usually selected empirically.

\[ \sum_k \frac{\left| \hat{R}_k^{n+1} - \hat{R}_k^n \right|^2}{\left| \hat{R}_k^n \right|^2 < \varepsilon. \]  

(8)

2.2. Nondominated Sorting Genetic Algorithm II (NSGA II). NSGA II is an improved multiobjective optimization method based on genetic algorithm. The NSGA II algorithm introduces the concepts of crowding degree and crowding distance operator on the basis of traditional sorting genetic algorithm. In the optimization process, samples are further selected through crowding degree to form a new parent population. Therefore, NSGA II can solve the problem of finding the optimal solution of various multiobjective functions. It has strong adaptability and high computing performance [30]. The basic flow of the NSGA II algorithm is shown in Figure 1.

The optimal solution group of multiobjective optimization can be obtained through the NSGA II method. This method has the characteristics of simple use and high efficiency, and its disadvantage is that it is unable to obtain a more accurate optimal solution vector. Based on the characteristics of the NSGA II method, this paper intends to use this method to screen the optimal solution set and quickly and effectively reduce the selection range of multiobjective optimal solution.

2.3. Multiobjective Particle Swarm Optimization Algorithm (MOPSO). The multiobjective particle swarm optimization algorithm introduces Pareto advantage into particle swarm optimization (PSO), so that PSO has the ability to optimize multiobjective function. The biggest advantage of this method is the use of mutation operator, which improves the global exploration ability of the algorithm [31]. The algorithm steps of MOPSO are shown in Table 1.

The MOPSO method can obtain the multiobjective optimal solution with ideal effect under the condition of reasonable parameters. This paper will effectively use the global parameter search ability of MOPSO to quickly obtain the optimal parameter vector within the optimal solution with limited range.

2.4. Signal Time-Frequency Domain Characteristics. In order to judge the decomposition effect of VMD, it is necessary to extract the signal features related to eigenmode groups (IMFs) to judge the decomposition effect. In order to verify the best signal feature indexes, this paper selects some features commonly used to evaluate the signal and uses \( X(t) \)
to represent the time series of the signal. Table 2 shows the commonly used feature indexes [32].

The characteristic index can be used to evaluate the fluctuation of vibration signal and the characteristics of time-frequency domain, so as to determine the specific components in the signal. The signal categories can be classified by extracting the characteristic indexes of different signals. At the same time, it also provides a method for further analyzing the signal components. By studying the correlation between different characteristic indexes and signal categories, signal processing can be used and methods to solve many practical engineering problems [33].

3. NSGA II-MOPSO VMD

3.1. Proposed Method. In order to realize the parameter optimization of VMD, this paper proposes a collaborative hybrid heuristic optimization algorithm—multiobjective particle swarm optimization algorithm with nondominated sorting (NSGA II-MOPSO). Firstly, the optimization target population is nondominated sorted to obtain the particle population with good and bad sorting, and then, the multiobjective particle swarm optimization algorithm is used to further find the optimal solution. This method combines the fast optimization of nondominated genetic algorithm and the high-precision optimization of particle swarm optimization algorithm, solves the problems of low optimization accuracy of nondominated genetic algorithm and low efficiency of particle optimization, and forms an efficient, adaptive, and robust algorithm combined with VMD optimization. The proposed algorithm flow is shown in Figure 2.

Figure 2 shows the specific process of optimizing VMD parameters by using the NSGA II-MOPSO method. First, determine the parameter selection range of the VMD method according to the actual situation, find the optimal
parameter vector within the value range, and decompose the fault components of the signal; first, obtain the dominant group of the optimal solution through NSGA II and reduce the global range of the MOPSO method, which can improve the accuracy of the optimal solution search efficiency, while further global search also ensures the accuracy of the method.

### 3.2. Method Validation

In order to verify the feasibility of the method, a group of analog signals are used to simulate the actual rolling bearing fault vibration signal to verify the effectiveness of the method. The analog signal function is shown in the following equation:

\[ x(t) = \sum_i A_i S(t - T_i) + n(t), \quad (9) \]

where \( S(t - T_i) \) represents the waveform generated by the \( i \) th pulse at time \( T_i \) and \( n(t) \) represents the random noise generated during vibration. In this paper, a group of signals with four vibration frequency components are simulated by using periodic pulse signal, and the formed simulation signal is shown in Figure 3.

The four vibration frequencies of the set simulation signal are, respectively, \( fn1 = 800 \), \( fn2 = 1600 \), \( fn3 = 2200 \), and \( fn4 = 4000 \). In addition, noise with a signal-to-noise ratio of -8 is added to the mixed signal to simulate external conditions. The obtained simulation signals are used to verify the VMD method, and different \( K \) and \( \alpha \) are verified, respectively, the peak factor, waveform coefficient, kurtosis, and the change of kurtosis factor. When the number of decomposed modes is 4, the signal characteristic index curve obtained is shown in Figure 4.

<table>
<thead>
<tr>
<th>Table 2: Some signal characteristics involved in this paper.</th>
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<tbody>
<tr>
<td><strong>Time domain characteristics</strong></td>
</tr>
<tr>
<td>Average value</td>
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<tr>
<td>( \mu_x(t) = \lim_{N \to \infty} \frac{1}{N} \sum_{i=1}^{N} x_i(t) )</td>
</tr>
<tr>
<td>Variance</td>
</tr>
<tr>
<td>( \psi_x^2(t) = \lim_{N \to \infty} \frac{1}{N} \sum_{i=1}^{N} x_i^2(t) )</td>
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<tr>
<td>Root mean square</td>
</tr>
<tr>
<td>( X_{rms} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} x_i^2(t)} )</td>
</tr>
<tr>
<td>Standard deviation</td>
</tr>
<tr>
<td>( X_{std} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i - \mu_x)^2} )</td>
</tr>
<tr>
<td>Peak coefficient</td>
</tr>
<tr>
<td>( C_f = \frac{X_{rms}}{X_{max} - X_{min}} )</td>
</tr>
<tr>
<td>Waveform coefficient</td>
</tr>
<tr>
<td>( C_s = \frac{X_{rms} \cdot \sum_{i=1}^{N}</td>
</tr>
<tr>
<td>Kurtosis</td>
</tr>
<tr>
<td>( C_k = \frac{1}{N} \sum_{i=1}^{N} x_i^4 )</td>
</tr>
<tr>
<td>Kurtosis factor</td>
</tr>
<tr>
<td>( C_{kf} = \frac{C_k}{X_{rms}^4} )</td>
</tr>
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</table>

**Figure 2**: NSGA II-MOPSO optimizing VMD parameter process.
Figure 4 shows that the characteristics change regularly with the penalty term $\alpha$; as the value increases, kurtosis, peak factor, waveform coefficient, and kurtosis factor tend to be stable, so it can be studied according to its variation law $\alpha$, the range of the best value method. In the characteristic curve, the characteristic curve at $\alpha = 1100$ has mutation. Take $\alpha = 800$ and $\alpha = 1700$ to test the mutation, respectively. The comparison diagram of the decomposition results before and after is shown in Figure 5.

Through the comparison of Figure 5, it can be found that in case $\alpha < 1100$, the VMD method cannot correctly divide the center frequency of the signal, and its decomposition result is unreliable, while in case $\alpha > 1100$, the decomposition result of VMD is basically consistent with the simulation actual frequency. Therefore, it also shows that among the above four eigenvalues, the peak factor, waveform coefficient, and kurtosis factor other than kurtosis can determine the parameters within the correct range. It can be seen from Figure 5 that the characteristic parameters with strong correlation with $\alpha$ value are peak factor and waveform coefficient. Therefore, this paper proposes characteristic mutation factor $C_m$ and accuracy index $C_a$ as the objective function of optimizing VMD parameters, respectively. The two characteristic expressions proposed are

$$C_m = \frac{N\sum_{t=1}^{N}X(t)^4}{(X_{\text{max}} - X_{\text{min}}) \cdot \left(\sum_{t=1}^{N}X(t)\right)^2},$$

Figure 3: Simulation signal. (a) Time domain diagram of simulation signal. (b) Frequency domain diagram of simulation signal.

Figure 4: Curve of signal correlation characteristics with quadratic penalty term $\alpha$ when $K$ takes 4.
The proposed characteristic mutation factor and accuracy index comprehensively consider the change trend of relevant indexes in Figure 4. When the parameter value is gradually close to the optimal solution, the value of the two eigenvalues will be stable at a certain level. Whether the optimal result is obtained in the optimization process can be judged by detecting whether the two groups of eigenvalues tend to be stable.

Therefore, the two characteristic parameters proposed in this paper will be used as the objective function of the NSGA II-MOPSO method, so as to realize the parameter optimization of VMD.

\[ C_a = \frac{\sum_{t=1}^{N} X(t)}{N(X_{\text{max}} - X_{\text{min}})}. \quad (10) \]

The proposed characteristic mutation factor and accuracy index comprehensively consider the change trend of relevant indexes in Figure 4. When the parameter value is gradually close to the optimal solution, the value of the two eigenvalues will be stable at a certain level. Whether the optimal result is obtained in the optimization process can be judged by detecting whether the two groups of eigenvalues tend to be stable.

Therefore, the two characteristic parameters proposed in this paper will be used as the objective function of the NSGA II-MOPSO method, so as to realize the parameter optimization of VMD.

3.3. Overall Improvement Method and Process. Firstly, the bearing signal is collected by the acceleration vibration sensor, the selection range of VMD parameters is set, and the characteristic mutation factor and accuracy index are taken...
as the objective function of the nondominated sorting genetic algorithm. Then, the parameter set is optimized by the nondominated sorting genetic algorithm. In this step, the nondominated sorting genetic algorithm can optimize the range of parameters, the disadvantage of this method is that it cannot quickly obtain the optimal data set, and its accuracy needs to be improved by multiple iterations, which greatly affects the optimization efficiency. The disadvantage of MOPSO is that if the parameter selection interval is too large and the number of particle swarm optimization and the number of iterations are limited, the optimization results are not reliable. Therefore, taking the preliminary screening data set of nondominated sorting genetic algorithm as the optimization interval of MOPSO can not only improve the optimization efficiency but also ensure the reliability of the results. The collaborative hybrid metaheuristic algorithm for VMD parameter optimization formed by combining the two advantages is shown in Figure 6.

4. Experiment

In order to verify the effectiveness of the proposed method, the actual data of the bearing data center of Case Western Reserve University in the United States are used to verify the method [34]. The experimental device and rolling bearing are shown in Figure 7.

The acquisition frequency of vibration signal is $f_s = 12$ kHz, the motor speed is set to $\text{rpm} = 1750$, the bearing model adopted is SKF6205, the fault type is 0.014 inch wide and 0.011 inch deep artificial pit inner ring fault, and a group of fault free experimental data is used as the control experimental group. The signal segment and its time-

![Figure 8: Time-frequency diagram of actual collected signal.](image)

![Table 3: Setting of parameter value in optimization algorithm.](image)

![Figure 9: Optimization results obtained with $C_m$ and $C_a$ as objective functions.](image)
equipment. When the rolling bearing has no fault and no external noise, K can be taken as 3. When the rolling bearing has compound fault and environmental noise interference, K may be taken as 8. Therefore, the range of K value is [3, 8]. The selection of quadratic penalty term coefficient α is based on the possible modal frequency range in the signal. By referring to the basic parameters of the experimental bearing, the value α is set within the range of [400, 5000]. $N_i$ represents the number of initial parameter groups, K and α represent the initial population number of vector combinations, and $N_n$ represents the size of the dominant data set processed by the NSGA II method. The initial population of the MOPSO method is the same as the dominant set obtained by NSGA II. Finally, a group of optimal parameter vectors are selected from the dominant set by the MOPSO method. There is only one optimal solution obtained by this method, so there is no problem of uneven distribution of the optimal solution. The experimental results also verify the reliability of the obtained optimal solution.

The parameter optimization results of this method are shown in Figure 9. The values of K and α corresponding to the best point are K = 5 and α = 2832. The decomposition results as shown in Figure 10 can be obtained by substituting the optimal parameter values into VMD. The inner ring fault frequency of the experimental bearing is calculated through equation (11) and compared with the obtained results to verify the effectiveness of the iterative dominant group and the fast iteration speed of MOPSO, but the optimization result is poor due to the rapid selection of the best. The NSGA II MOPSO method used in this paper is relatively fast in speed and can ensure reliable operation results, so the method proposed in this paper is feasible.

5. Conclusion

This paper mainly optimizes the parameter selection method of VMD and completes the VMD parameter optimization of rolling bearing vibration signal by using the NSGA II MOPSO multiobjective optimization algorithm. In addition, by analyzing the change of signal waveform characteristics, the characteristic mutation factor and accuracy index are proposed, and the new index is used as the objective parameter.
function to optimize the parameter selection. The effectiveness and the advanced nature of the method are verified by comparison. The main contributions of this paper are as follows:

(1) The practical performance of the cooperative hybrid metaheuristic algorithm is studied. The NSGA II and MOPSO are combined to optimize the VMD of rolling bearing signals, which proves the advanced nature of the cooperative hybrid metaheuristic algorithm.

(2) The relationship between the waveform characteristics of signal modal decomposition results and VMD parameters is studied, and two characteristics of characteristic mutation factor and accuracy index are proposed to be used in parameter optimization. The performance of characteristics in VMD optimization is verified by experiments.

(3) A complete process of optimizing VMD parameter selection using NSGA II MOPSO is proposed. This method is compared with other parameter optimization methods to verify the improvement of the proposed method in adaptive ability, operation speed, and robustness.

Data Availability

The data is not publicly available and therefore cannot be provided.

Conflicts of Interest

The author declares no conflicts of interest.

Authors' Contributions

Zhou Guifan wrote the paper and processed the data.

References


[34] The data is from the bearing data center of Case Western Reserve University, USAWebsite: https://csegroups.case.edu/.